

Mobility Prediction via Markov Model in LTE Femtocell

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ABSTRACT

Seamless handover is one of the main goals in Long Term Evolution (LTE). In order to achieve a seamless handover, the handover latency needs to be reduced. By predicting where the users are moving, the resource allocation can perform prior to the actual handover, thus can reduce delays in resource allocation and finally can reduce the handover latency. In LTE femtocells network, the large number of femtocells may deploy in a single macrocell, therefore the number of targets femtocell during the handover process is huge. Hence, the prediction of users' direction is expected to reduce the scanning time and the handover latency during handover process. This paper performs the mobility prediction relying on Markov Chain. The results show the prediction of users' direction after several movements. Based on the results, we can conclude that the main parameter that influence the prediction is a transition probability matrix. Therefore, this value should be determined properly in order to get the most accurate prediction.

General Terms

Long Term Evolution, Femtocells, Mobility Prediction, Markov Chain.

Keywords

LTE, Markov Chain.

1. INTRODUCTION

Due to high demand of high data rate in wireless communication and emergence of new application such as Multimedia Online Gaming, Mobile TV, 'e' application, online banking, and Web 2.0 (i.e. Facebook, myspace), the Third Generation Partnership Project (3GPP) has introduced the Long Term Evolution (LTE). LTE is the latest standard in the mobile network technology tree that previously realized the GSM/EDGE and UMTS/HSxPA network technologies that now account for over 85% of all mobile subscribers [1]. LTE is expected to improve end-user throughput and sector capacity, reduce user plane latency, and improved user experience with full mobility. LTE has been designed to provide a high data rate which is 100Mbps for downlink and 50Mbps for uplink. The LTE performance requirements can be seen in [2] for more detail.

As per survey on wireless usage, more than 50% of all voice calls and more than 70% of data traffic originates indoors [3]. Therefore, it is extremely important for cellular operators to provide good indoor coverage to fulfill the customer needs. Due to this reason, the femtocell has been introduced in 3GPP Release 8 [4] in order to extend the coverage and increase the system capacity in indoor environments. The femtocell is low-power wireless access points that operate in a licensed spectrum to connect standard mobile devices to a mobile operator's network using residential digital subscriber line

(DSL) or cable broadband connections (see Figure 1). The femtocell is designed as a friendly user device and must be plug-and-play device since it is installed by the customer or subscriber. The power range of the femtocell is between 13 ~ 20dBm, in the same floor, the maximum coverage is about 15 to 50 meters (location and the actual environment would affect the coverage) [5].

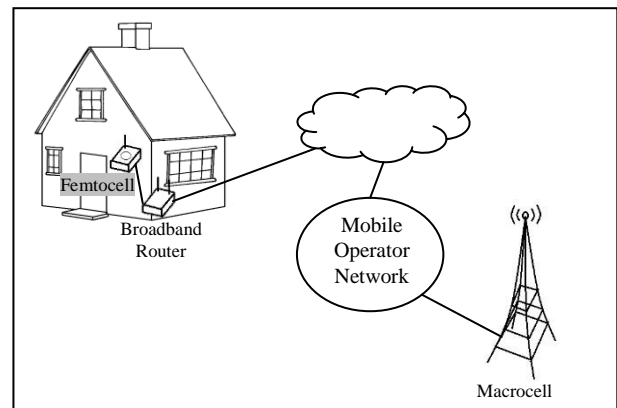


Figure 1: The basic structure of femtocell

One of the main goals of LTE is to provide fast and seamless handover from one cell to another cell. In order to achieve these goals and reduce the complexity of the LTE architecture, hard handover is implemented in LTE, which all the old radio links in the user equipment (UE) are removed before the new radio links are established. For handover procedure, as less number of scanning and signaling flows as possible should happen to reduce the power consumption as well as to make the handover fast [6]. The characteristic of femtocell that deploy by end-user lead a large number of femtocell in single macrocell, therefore there are many possible target femtocells in femtocell network. As shown in Figure 2, the user may pass by the femtocells in a short time and lead frequent handover. In handover procedure, the UE needs to make a measurement of the Received Signal Strength Indicator (RSSI) of the neighboring cells. Since there are many possible target femtocells, the UE needs more time to scan the appropriate cell. This long scanning interval increases the packet jitter and end-to-end delay, thus improving large buffer sizes. Therefore it is necessary to reduce the scanning time of RSSI. By knowing where the UE is going, the target base station can be predicted and finally can reduce the scanning time as well as the handover latency.

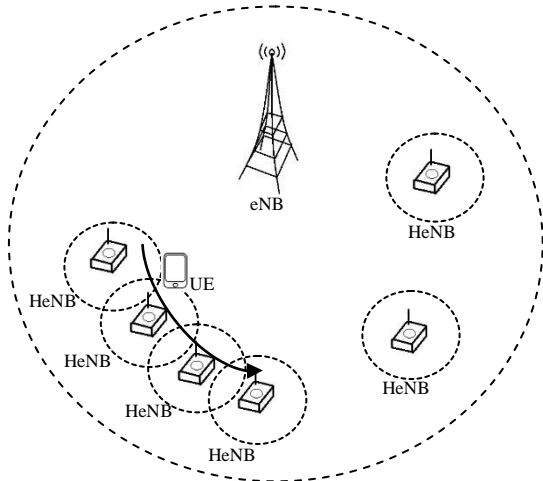


Figure 2: Frequent handover in LTE Femtocells network

In this paper, we discuss the mobility prediction in an LTE Femtocell network. The paper is organized as follows: Section II describes the related work on mobility prediction in wireless network and overview of prediction via Markov Chain. Section III discusses the proposed work on mobility prediction via Markov Chain. Finally we conclude this paper in Section IV.

2. MOBILITY PREDICTION IN WIRELESS NETWORK

2.1 Related Work

Whenever the users are moving, the call needs to be handover to the new base station, and network resources must be reallocated. During the handover procedure, resource allocation takes a lot of time and becomes the main factor of handover latency. In order to achieve a seamless and fast handover, the handover latency needs to be reduced. One of the most effective techniques to reduce delay in resource allocation and finally reduce the handover latency is by predicting the next location of the users. Mobility prediction detects the identity of the future cell for resource reservation prior to the actual handover [7].

Several researches have been done on mobility prediction to enhance the handover performance in wireless networks. One of the parameters to be considered in order to evaluate the handover performance is the number of handover. Each handover consumes network resources to reroute the call to the new base station (BS), therefore minimizing the expected number of handover will effectively minimize the signaling overhead which is needed for different UE speeds [8]. In [9], the authors have proposed a prediction technique based on users' mobility history. In this proposed technique, the network shall recognize the users who frequently visit the cell, and then track and records the movement information of the user. According to the information and the location of the user, the network is able to search a route of the user. The signal strength is considered to choose the handover candidate. This proposed technique can minimize the number of handover and lower the ping-pong rate in LTE systems, however it only can be implemented for regular users.

In [10], the authors have proposed a prediction technique relying on Markov Chain. The proposed technique has considered the position-based path prediction as a technique to predict the target cell of the users. By knowing the position and velocity of the users, it can help to guess where the user is heading and finally can predict the next cell. In this prediction

method, it is assumed that the user is able to send its location periodically to the serving base station, and at the same time the serving base station is able to maintain a database of the roads within its coverage. The prediction is strongly relied on transition probability matrixes, and several values of transition probability matrixes are simulated. Based on Markov Process, the form of the user's movement (i.e. linear, reside, random, and patterned) can be predicted as well.

Lastly in [11], the authors have proposed a mobility prediction strategy based on modeling a mobile user's behavior by a colony of ants. The strategy is inspired by the ants' behavior during their search for food where the ants will follow the most attractive route to find its food. This is determined by the quantity of pheromone that deposits by other ants. The higher the pheromone intensity, the most attractive route is. Based on this strategy, the current base station need to update its user's history displacements and predict their future positions according to their current position and their habits. If a new user enters the system and the base station does not have its history, the base station can use the history of other users that have a same mobility profile. The advantage of this strategy is it can predict the next location of the user not only for regular users, but also for non-regular user that first time enters the system.

2.2 Prediction via Markov Chain

One of the existing prediction technique in a wireless network is predicted via Markov Chain. Markov Chain is a mathematical system that undergoes transitions from one state to another. It is a random process and usually characterized as memoryless; which means the next state depends only on the current state and not the sequence of events that preceded it. Markov Chain is a transition system composed of:

1. A set of states $S = \{s_1, \dots, s_n\}$; in which each state corresponds to a base station (or a set of base stations).
2. A set of transitions; in which each transition represents a movement from the state.

If the Markov Chain has n state, the dimension of transition probability matrix P will become $n \times n$:

$$P = \begin{bmatrix} p_{11} & \dots & p_{1n} \\ \vdots & \ddots & \vdots \\ p_{n1} & \dots & p_{nn} \end{bmatrix}$$

The values of transition probability matrix P are derived from a diagram called state Markov Chains diagram. Figure 1 below shows the relationship between state Markov Chains diagram and transition probability matrix P .

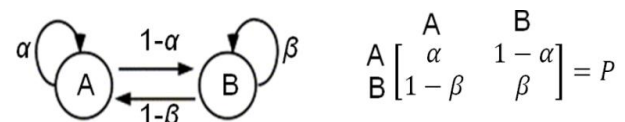


Figure 3: Relationship between state Markov Chains diagram and transition probability matrix P

From Figure 3, two states A and B are considered, therefore the transition probability matrix become 2×2 . The value of α is probability the user moves from state A to state A, and the value of $(1 - \alpha)$ is probability the user moves from state A to state B, and same concept for others. The summation of the row is equal to 1, means the summation of α and $(1 - \alpha)$ is equal to 1.

Besides the transition probability matrix P , the parameter needs to be considered in Markov Chain is initial distribution

matrix p . The value of initial distribution matrix can be derived from users' velocity, distance, or initial state. In this paper, we consider the users' initial state as the value of an initial distribution matrix. Hence, we can determine the path of the users since their initial state until it reaches the stable state where we consider it as users' final state. If the number of states is two as described in Figure 3, the value of initial distribution become 1×2 :

$$p = [a \quad b] \quad (1)$$

Therefore, the position of the user after n movement can be derived as:

$$p_n = [p] x [P_{n-1}]^n \quad (2)$$

where,

p = initial distribution,

P_{n-1} = current transition probability matrix,

n = number of state transition.

3. PROPOSED WORK

3.1 Scenario

In this paper, we consider three base stations which are eNB, HeNB1, and HeNB2. Figure 4 shows the considered scenario and the transition probability matrix P . Since there are three base stations, the transition probability matrix becomes 3×3 . The initial distribution matrix p is derived from users' initial state. This value is important because we can predict the next position of the user since the early stage.

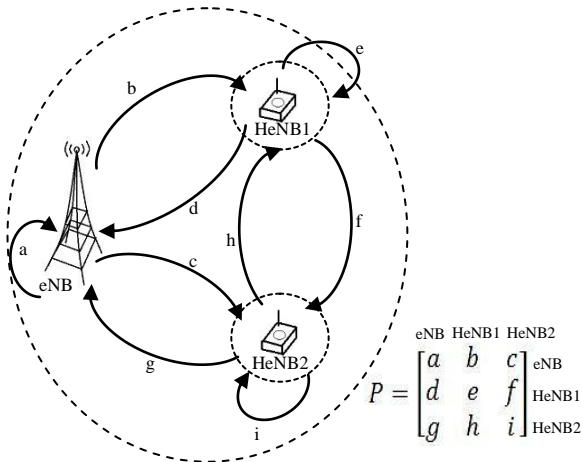


Figure 4: The transition probability matrix of considered scenario

3.2 Simulation

The simulation has been done in MATLAB to determine the movement of the users by using Markov Chain. There are four values of the transition probability matrix have been used in this simulation and can be found in Table 1. These values of the transition probability matrix are assumed and the number of state transition, n is 10 states. There are three users have been considered with difference initial distribution matrix and can be found in Table 2. These values are referring to the initial state of the user. For example, for UE_1 the value is $[1 \ 0 \ 0]$ and it means that the UE_1 is at eNB at first place. For values $[0 \ 1 \ 0]$ and $[0 \ 0 \ 1]$, they are referring to HeNB1 and HeNB2, respectively. It is assumed that the eNB has highest priority state, means if the values are same for both or all states, the result should be eNB.

Table 1. Transition probability matrix

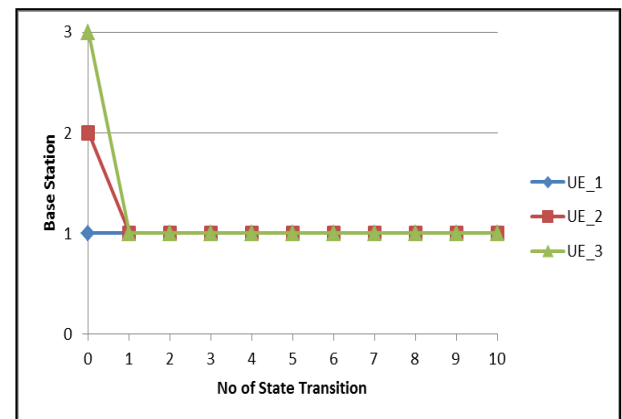
Matrix	Values
tpm ₁	$\begin{bmatrix} 1/3 & 1/3 & 1/3 \\ 1/3 & 1/3 & 1/3 \\ 1/3 & 1/3 & 1/3 \end{bmatrix}$
tpm ₂	$\begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$
tpm ₃	$\begin{bmatrix} 0 & 0.3 & 0.7 \\ 0.5 & 0 & 0.5 \\ 0.4 & 0.6 & 0 \end{bmatrix}$
tpm ₄	$\begin{bmatrix} 0 & 0.7 & 0.3 \\ 0 & 0.5 & 0.5 \\ 0.3 & 0.3 & 0.4 \end{bmatrix}$

Table 2. Initial Distribution Matrix

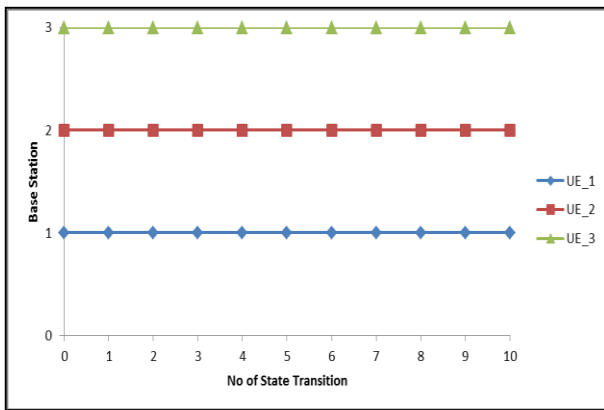
Matrix	Values
UE_1	$[1 \ 0 \ 0]$
UE_2	$[0 \ 1 \ 0]$
UE_3	$[0 \ 0 \ 1]$

3.3 Result and Discussion

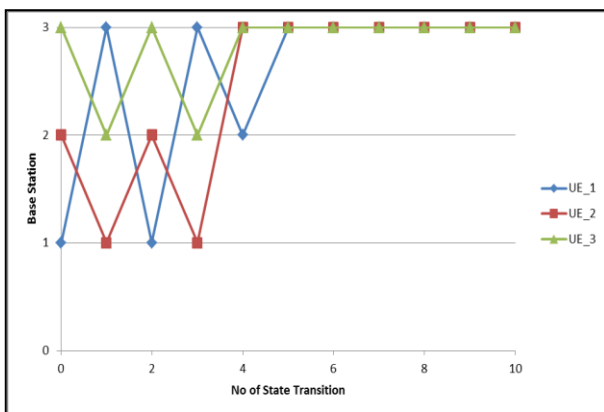
The simulation has been done to predict the next position of the user by using Markov Chain techniques based on a transition probability matrix as stated in Table 1. The results have been plotted in graph as shown in Figure 5. The base stations 1, 2 and 3 are referring to eNB, HeNB1 and HeNB2, respectively. The results show the predicted base station for three users starting from their initial state.



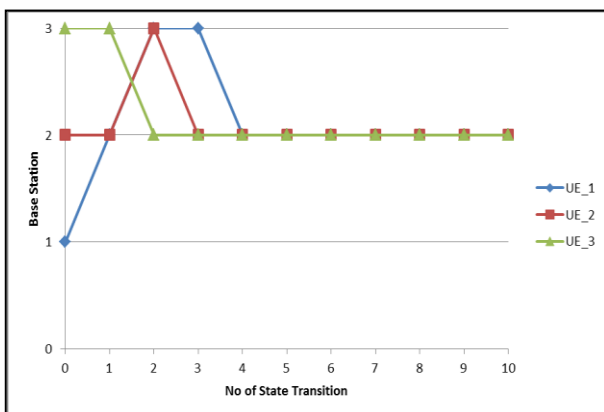
a) Prediction result for tpm₁



b) Prediction result for tpm₂



c) Prediction result for tpm₃



d) Prediction result for tpm₄

Figure 5: The prediction results of users' direction after several movements

From the graphs, we can see that the users will go to the same base station after several movements regardless of the initial state, except for tpm₂. This is because of the type of transition probability matrix tpm₂ is in the identity matrix type in which the diagonal elements are equal to 1. It means the user is moving to the same base station, or in other words the users are not moving to another base station. For tpm₁, the value of the transition probability matrix is same (i.e. 1/3), but since we assume that the eNB has higher priority than others base stations, therefore all users are predicted to move to eNB.

Another simulation has been done where we consider four users with same initial distributions which is [0 1 0] (i.e. HeNB1) but difference transition probability matrix. The

UE₁ is using transition probability matrix tpm₁, the UE₂ is using tpm₂, the UE₃ is using tpm₃, and the UE₄ is using tpm₄. Figure 6 shows the results of users' direction after several movements. From the graph we can see that the users' direction is different from each other even though the initial state is same. Based on all results, we can conclude that the mobility prediction is strongly relying on transition probability matrix.

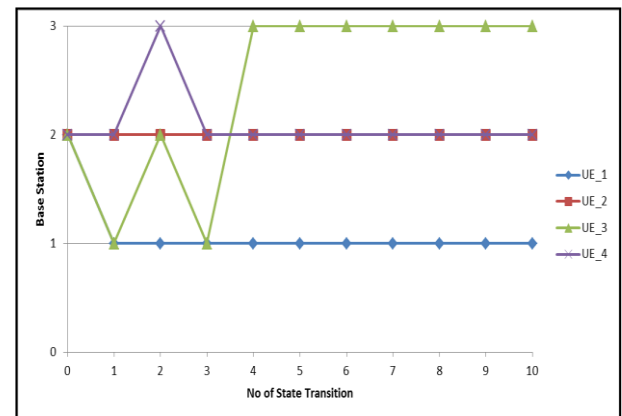


Figure 6: The prediction results of users' direction after several movements for varying transition probability matrix

4. CONCLUSION AND FUTURE WORKS

Mobility prediction has been proved as a technique to improve the handover performance. It can provide service for mobility management, call admission control, smooth handovers, and resource reservation. One of mobility prediction technique in a wireless network is predicted via Markov Chain. This paper has performed a mobility prediction in LTE femtocells network via simple Markov Chain technique. The results show the next position of the users after several movements.

The results show that the main parameter that influences the prediction is a transition probability matrix. Thus, this value should determine properly in order to get the most accurate prediction. The inaccuracy on the value of the transition probability matrix will cause an incorrect prediction and may cause a handover failure. In this paper, the value of the transition probability matrix is assumed. Therefore, next study on mobility prediction is on determination of human behavior as an input to the transition probability matrix.

5. ACKNOWLEDGMENTS

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6. REFERENCES

- [1] Motorola, 2007. Long Term Evolution (LTE). Technical White Paper.
- [2] Motorola, 2007. Long Term Evolution (LTE): A Technical Overview. Technical White Paper.

- [3] Chandrasekhar, V. and Andrews, G. 2008. A. Femtocell Networks: A Survey. IEEE Communications Magazine.
- [4] 3rd Generation Partnership Project. [Online]. Available: <http://www.3gpp.org/Release-8>.
- [5] Wu, S. J. 2011. A New Handover Strategy between Femtocell and Macrocell for LTE-Based Network. In Proceedings of the 4th International Conference on Ubi-Media Computing (U-Media).
- [6] M.Z. Chowdhury, Y.Jang, “Handover Control for WCDMA Femtocell Networks”, Journal of Korea Information and Communication Society, 2010.
- [7] T. Duong, D. Tran, “An Effective Approach for Mobility Prediction in Wireless Network based on Temporal Weighted Mobility Rule”, International Journal of Computer Science and Telecommunications, vol. 3, no. 2, 2012.
- [8] Hussein, Y. S., Ali, B. M., Varahram, P. and Sali, A. 2011. Enhanced Handover Mechanism in Long Term Evolution (LTE) Networks. Scientific Research and Essays.
- [9] Ge, H., Wen, X., Zheng, W., Lu, Z. and Wang, B. 2009. A History-Based Handover Prediction for LTE Systems. In Proceedings of the 4th International Conference on Ubi-Media Computing (U-Media).
- [10] Ulvan, A., Ulvan, M. and Bestak, R. 2009. The Enhancement of Handover Strategy by Mobility Prediction in Broadband Wireless Access. In Proceedings of the Networking and Electronic Commerce Research Conference (NAEC 2009).
- [11] M. Daoui, A. M’zoughi, and M. Lalam, “Mobility Prediction based on an Ant System”, Journal of Computer Communications, vol. 31, pp. 3090–3097, 2008.